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Yard block assignment, internal truck operations, and berth allocation in container terminals: introducing carbon-footprint minimisation objectives

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Abstract

It is of increasing importance to carry out port terminal operations in an environmentally sustainable way. We approach the yard block assignment and internal transportation problem in a way that establishes an optimum trade-off between the time of internal truck moves and environmental objectives. The framework has a dynamic structure and aims to offer different berthing alternatives according to yard block occupancy rates. Earlier limitations of deterministic modelling are addressed. Probabilistic methods are considered in an attempt to bring our outcomes closer to real terminal circumstances. Discrete Monte Carlo simulation, integer-linear programming and multi-objective optimisation methods are integrated to address container terminal modelling complexity. The uncertainty arising from situations such as irregular vehicle queuing at the yard or quay crane stations is successfully addressed. The opinions of managers involved in decisions regarding the 'time–environment dilemma' are weighted and included in the optimisation model. In five scenarios, we show that internal truck time efficiency can improve by 27.8% to 42.8%, and CO_2 emissions reduction by 30.1% to 70.3%.

Keywords Carbon footprint minimisation · Container terminals · Monte Carlo simulation · Port management · Yard block assignment · Berth allocation

1 Introduction

In 2019, 793.3 million TEUs were handled by world ports, entailing an average annual growth of 3.4% between 2019 and 2024 (UNCTAD 2019). Such massive volumes of cargo handled at container terminals obviously generates significant atmospheric emissions accompanied by impacts only too well known. That said, efforts

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of the port industry to 'green' its profile are also noticeable and have started to pay fruit.

There is a vast number of studies on the optimisation of terminal operations. Most of them generally include yard crane (YC), quay crane (QC) and yard truck (YT) scheduling, as well as berth allocation and yard storage allocation issues. These sub-processes are heavily interdependent (Zhen et al. 2016a; b). In the literature, QC performance is generally referred to as one of the bottlenecks of terminal operations, and QC productivity is invariably emphasised (Zhang et al. 2015), depending in its turn on YT transportation time. Therefore, in this study, internal yard truck transportation is considered as another bottleneck in terminal operations. Yard truck transportation time (YTTT) represents the time to move a container between the berth and the yard block. Yard trucks are the primary source of the terminal's CO_2 emissions (Yu et al. 2017). The YTTT value is affected by the distance travelled between yard blocks and berth, the traffic density in the terminal area, the number of deployed YCs in blocks, and the queuing time in YC/QC stations. For this reason, yard pattern (Petering 2009) and yard storage allocation (Jin et al. 2014) are essential in terms of the effectiveness of terminal operations. At present, a shortcoming in the extant literature is that the 'yard vacancy' variable is mostly ignored. Yard vacancy data for each sub-block is however of importance for effective container allocation. It is necessary (but, as we argue here, not sufficient) for a realistic model to draw the empty yard layout before venturing into the optimisation model.

Berth distances from yard blocks are different, and terminals operate different types of trucks that differ from each other in terms of fuel consumption and CO_2 emissions. The problem of berth selection could thus be the attempt to optimise internal truck movements in terms of transport time and emission costs. In other words, in allocating a berth to a ship, the management needs to decide on the trade-off between GHG emissions and the duration of truck operations. Two critical factors are thus evaluated simultaneously: minimise the carbon footprint of truck movement and minimise the time of track operations.

We propose a framework that can be used for the berth allocation problem that considers both environmental objectives and operational priorities. The framework has a dynamic structure and aims to offer different berthing alternatives according to yard block occupancy rates. This study approaches the yard block assignment and internal transportation issues holistically and realistically by focusing on operational and environmental factors. More specifically, we employ Monte Carlo Simulation to predict the average vacancy of container blocks and queuing times at the YC and QC. This, then, is input to the subsequent optimisation model. Next, a linear integer programming model is built with the objective to minimise yard truck time and carbon-footprint. This step gives answers to: (i) How many containers will be transported to which sub-block? (ii) Which type of vehicle[1] will be used for how many times?

[1] The type of vehicle refers to the trucks that differ from each other in terms of fuel consumptions and CO_2 emissions.

For each berth, the optimisation problem is solved for the minimum transportation time and CO_2 emissions. Findings obtained without weighing the 'time–footprint' trade-off are insufficient to provide decision support as to which berth should be selected for an incoming ship, with the scope of optimising internal truck operations. Managers should therefore determine a priori the relative importance of these two criteria, i.e., time and carbon footprint. For this purpose, the analytical hierarchy process is utilised, and the decision-making (DM) group is selected out of C-level and senior-level terminal managers, as this issue represents a strategic decision. Finally, a multi-objective optimisation method, MOORA, is employed, for selecting the berth of an incoming ship, by considering the importance ratings of the two criteria.

Our contribution to the literature is as follows: (i) we provide an optimum solution to the trade off between truck time costs and environmental impacts and (ii) we address the complexity of port operations through probabilistic methods. The vacancy of yard blocks and the total time spent the terminal vehicles at the QC/YC stations are included in the model, with three discrete Monte Carlo simulations, based on historical data. Monte Carlo simulation is utilised in three discrete stages, bringing the model closer to the complexity of actual port operations. Probabilistic optimisation models are very scarce in the literature (Gupta et al. 2017). What makes our study different is its holistic approach, proposing a framework of analysis, rather than focusing only on a part of the problem. Instead, the main problem is divided into sub-problems and thoroughly analysed. Thus, a holistic evaluation is made by synthesising the sub-problems.

The rest of the study is structured as follows: Sect. 2 is dedicated to the review studies on equipment scheduling optimisation and terminal yard management. The definition of the research problem is given in Sect. 3. The methodology, assumptions and solution approach are presented in Sect. 4. Section 5 is devoted to results and, finally, the study concludes with Sect. 6, which discusses our contributions.

2 Literature review

Optimisation studies related to container terminal operations generally include QC, YT, YC scheduling, berth allocation, yard storage design and yard allocation topics. In what follows, the literature is examined under two headings, according to our methodology: (a) equipment (YT, YC and QC) scheduling and optimisation studies and (b) yard storage design and optimisation studies.

2.1 Equipment scheduling and optimisation

There is a vast number of studies on equipment scheduling, generally including combinations of two or more of QC, YC and YT equipment. In their study, Zeng and Yang (2009) propose simulation and optimisation algorithms for QC, YC and YT scheduling for minimising the duration of loading and unloading operations. He (2016) established his model focusing on a trade-off between two management strategies, namely time-saving and energy-saving. The author proposed a mixed integer programming model (MIP) and integrated optimisation and simulation method for the QC assignment and berth allocation problem.

Zhen et al. (2016a, b) addressed the integrated QC and YT scheduling problem, utilising particle swarm optimisation (PSO). The method reduced computation time by 47.78% in solving the optimisation problem. Chen et al. (2013) examined, via a heuristic approach, crane handling (QC/YC) and YT routing problems to improve overall efficiency by increasing coordination between terminal equipment. In the first stage of that study, the crane scheduling data are obtained and subsequently used in the second stage of the study to solve the YT routing problem. Zhang et al. (2015) discussed double-cycling to improve the operational performance of the terminal. Here, the working sequence is established between QCs and YCs to minimise operational time, while the YT assignment is not considered.

Lu et al. (2016) developed the PSO algorithm in a QC/YT scheduling optimisation model. The authors considered YT travel speed and QC handling speed elements as uncertain factors that determine the terminal's operating efficiency. The aim of the model was to minimise QC handling time with an effective YT allocation.

2.2 Yard storage management

Yard management problems are discussed in different ways in the literature. These can be grouped into two main categories: container allocation and yard template design. Zhen et al. (2016a; b) developed a yard template model with particle swarm optimisation (PSO), for cases of yard traffic congestion and various vessel arrival patterns. Petering (2009) used discrete event simulation to study yard designs of varying block widths. The paper found that the optimal block width varies between 6 and 15 rows, depending on handling equipment used, and terminal cargo throughput. Gupta et al. (2017) examined yard template design from the viewpoint of its direction, i.e., being perpendicular or parallel to the quay. An integrated queuing model was used. The authors concluded that a parallel design provides an advantage over a vertical one (4–12% improvement in throughput handled). Tan et al. (2017) proposed a flexible design to increase operational efficiency, instead of a fixed yard layout. In summary, the current literature regarding equipment scheduling and yard management practices is presented in Table 1.

3 Problem definition

The scenario begins with the berth selection problem for an incoming ship carrying 1500 TEUs. An operations manager needs to decide which berth would be the optimum, in terms of satisfying minimum truck time and minimum carbon footprint. Before assigning a berth, the management needs to first determine the availability of empty yard slots, as well as the transportation means that could do the job efficiently and with minimum environmental impact. Berthing plans of scheduled vessels can be done in few days to a week in advance. Considering this time frame, the future

Table 1 Equipment scheduling optimisation studies

Yard scheduling optimisation studies			
Study	Method	Aim	Source
Integrated QC-YC-YT scheduling problem	Integrated simulation and optimisation algorithms	Time minimisation	Zeng and Yang (2009)
Truck optimisation problem	Non-stationary vacation queuing model	Time minimisation	Zhang et al. (2019)
Integrated QC-YC-YT scheduling problem	MIP(GA, PSO), Simulation	Energy consumption	He et al. (2015a, b)
Integrated QC-YC-YT scheduling problem	A three-stage algorithm is developed with a heuristic approach	Time minimisation	Chen et al. (2013)
Integrated QC-YT scheduling problem	MIP(GA, PSO)	Time minimisation	Zhen et al. (2016a, b)
Integrated QC-YC scheduling problem	MIP, bi-level GA	Time minimisation	Zhang et al. (2015)
Integrated QC-YT scheduling problem	PSO, MUF (model with uncertain factors)	QC operating time	Lu et al. (2016)
Berth allocation and QC assignment problem	MIP, Simulation	Time and energy consumption	He (2016)
Berth allocation and QC-YT assignment problem	Multi-objective nonlinear mixed-integer programming	CO_2 emissions	Wang et al. (2019)
Berth allocation problem	MIP(GA, PSO)	Total waiting and handling time minimisation	Babazadeh and Shahbandi (2015)
YC scheduling problem	MIP (GA, PSO)	Time and energy consumption	He et al. (2015a, b)
YC scheduling problem	MIP	Time minimisation	Fatemi Ghomi et al. (2014)
YC scheduling problem	Integer programming	Energy consumption	Mei Sha et al. (2017)
QC assignment problem	Queueing model	CO_2 emission	Liu and Ge (2018)
Yard management optimisation studies			
Study	Method	Aim	Source
Yard template planning	MIP, PSO	Transportation cost minimisation	Zhen et al. (2016a, b)
Storage allocation and YC deployment	Integrated optimisation model	Time and transportation cost minimisation	Jin et al. (2014)
Optimum yard layout problem	Discrete event simulation	GCR maximisation	Petering (2009)

Table 1 (continued)

Yard scheduling optimisation studies

Study	Method	Aim	Source
Optimum yard layout problem	Queuing network modelling	Time minimisation	Gupta et al. (2017)
Yard storage planning problem	MIP	Workload imbalance minimisation	Li (2018)
Optimum yard layout problem	Integrated optimisation model	Space utilisation and operating cost minimisation	Tan et al. (2017)
Re-marshalling and yard storage planning	Genetic algorithm	Cost minimisation	Kim et al. (2019)
Terminal layout design	Literature review	N/A	Gharehgozli et al. (2020)

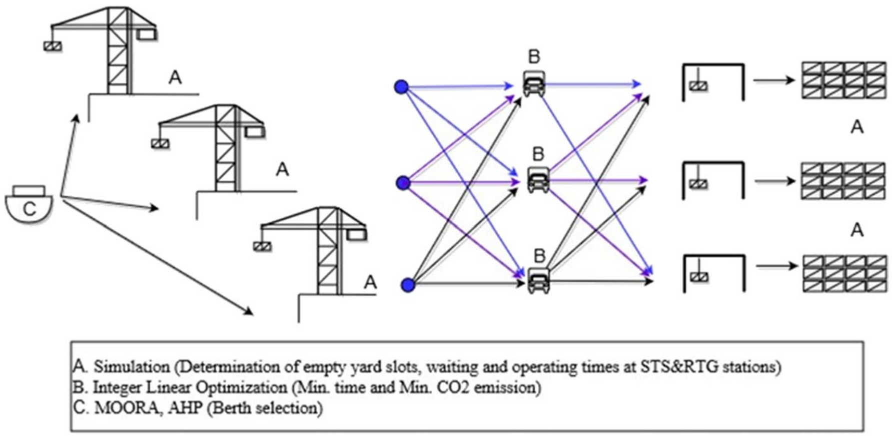

Fig. 1 Problem definition

occupancy rate of the yard blocks/sub-blocks may be uncertain due to various factors such as the irregular arrival patterns of ships, irregular dwell times of import containers and other changes that lead to an uncertain impact on yard occupancy ratio. Therefore, it is necessary to estimate the average occupancy rate for the future through simulation.

The next problem is to assign terminal trucks to the terminal blocks simultaneously, based on the management's 'transport-footprint' trade off decision. The optimisation issue to confront here is that the truck waiting time at YC/QC stations is not known. We forecast this using probabilistic methods. The integrated solutions of yard block assignment and internal transportation problems guide the decision-maker to choose an appropriate berth for an incoming vessel.

The terminal has three berths, three types of trucks with different fuel consumptions and CO_2 emissions, and 11 blocks, each with 18 sub-blocks,[2] illustrated in Fig. 1. The following assumptions are made for the specification of the problem:

- The route between each sub-block and each berth is fixed.
- Trucks move seamlessly without obstructing each other.
- The containers are considered homogeneous (TEU). Each yard truck carries one TEU at a time.
- Yard truck travel speed is set since there is a speed limit within the terminal.
- Variation in truck fuel consumption (depending on the status of a container, i.e., loaded or empty) is not taken into account.

[2] Port authorities do not consent to the disclosure of the terminal name.

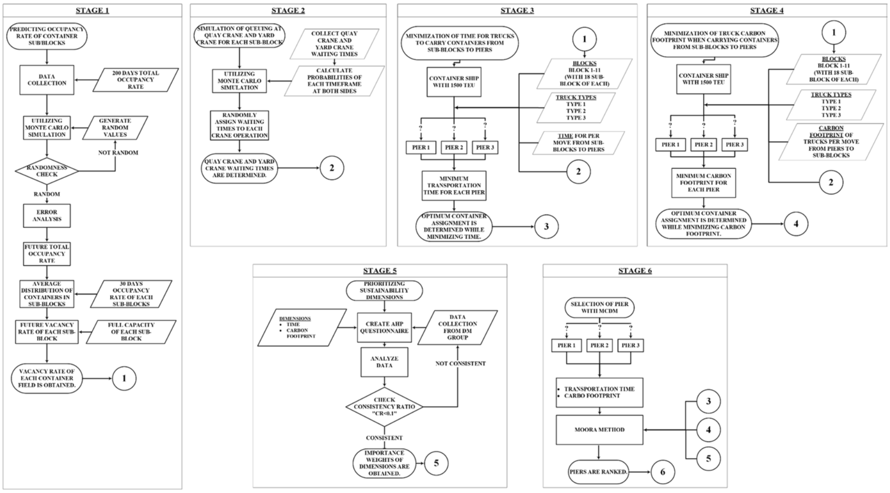

Fig. 2 Solution approach

4 Solution approach

This study is designed in stages, as shown in Fig. 2. The aim is to optimise internal truck operations, considering our 'time–footprint' trade off policy. The problem is divided into sub-problems, so that a solution is developed accordingly for each. Then, the main solution is obtained by synthesising each sub-solution, which yields to selecting a berth for an incoming ship.

In stage 1, Monte Carlo simulation estimates the average future occupancy/vacancy of container blocks based on historical data. The importance of conducting this analysis is obvious, since berth planning is done days before ship arrival. In stage 2, we take into account truck idling times at quay and yard, again via Monte Carlo simulation (trucks spend time and fuel while idling). In stages 3 and 4, berth-block truck movements are minimised, including the number of containers to be moved by each type of truck. In stage 5, the time and footprint criteria are weighed through analytical hierarchy process (AHP). In stage 6, a multi-objective optimisation method (MOORA) is utilised, using time and carbon footprint data from linear programming and the time–footprint weights from AHP to select the berth for the incoming containership. Besides, randomness due to truck waiting times at quay and yard crane queues is considered to influence the berth selection decision, and this needs to be demonstrated. Therefore, a series of analyses from stages 2 to 6 are carried out to eliminate deviation of randomness and validate the stability of the methodology.

4.1 Stage 1: predicting average occupancy rate of container blocks by Monte Carlo simulation

Monte Carlo simulation is used to generate random case scenarios through computer models (Takeshi 2013; Kroese et al. 2014). As the random case scenarios

Table 2 Frequency distribution of container yard occupancy

Number of categories	Occupancy range	Frequency of occupancy	Probability of occupancy ($P(x)$)	Cumulative probability	Random number interval
1	4150–4250	5	0.025	0.025	0–25
2	4251–4350	4	0.02	0.045	26–45
⋮	⋮	⋮	⋮	⋮	⋮
50	9051–9150	1	0.005	1.00	996–1000
		$\Sigma = 200$	$\Sigma = 1$		

are repeated many times, the result is a steady-state condition (Tekiner et al. 2010, Taylor III and Bernard 2013) as intended. Monte Carlo simulation is a widely preferred, easy and efficient technique, whereas randomness gives the flexibility to better understand the probabilities (Kroese et al. 2014).

As regards block occupancies, first the container throughput of 200 days in our case port is obtained and organised in a frequency distribution (Table 2).

Subsequently, 5000 random numbers are generated, and the corresponding occupancy range is determined for random data which satisfies the randomness rule since p $(0.821) > 0.05$. Thus, we use the middle number of each occupancy range, for instance 4200 containers for category 1, to determine the total number of containers in that simulated case. The average occupancy of the blocks for 5000 simulated cases is found to be 6479 containers. This value is validated by sampling error calculations. Therefore, the sampling error is calculated as 34 (for 5000 sampling data points, with a standard deviation of 1218). Thus, population mean will be between X_{max} (6513) and X_{min} (6445), with a 95% confidence level (Taylor III and Bernard 2013). In conclusion, the sample mean is used for future average yard occupancy. Container blocks are divided into sub-blocks, each with its own capacity. Thus, it is necessary to distribute the predicted average occupancy rate into sub-blocks evenly, as in the historical data. The total capacity of each container sub-block is known, and thus, the vacancy of sub-blocks is calculated.

4.2 Stage 2: introducing truck idling times at quay- and yard-crane queues

To determine truck idling times at the quay- and yard-crane queues with Monte Carlo simulation, the time each of the 150 trucks waited in the queue has been recorded. The probabilities of time spent at quay and yard were calculated by following the steps described in the previous section and randomly distributed to each berth and sub-block. Idling time was added to truck operation time. The corresponding carbon footprint was also counted as an idling emission value. Figure 3 shows all the steps in which the Monte Carlo method was utilised. These three stages reflect the uncertainty factors related to queue and equipment failure at YC/QC stations, and future uncertainties regarding utilisation of yard blocks.

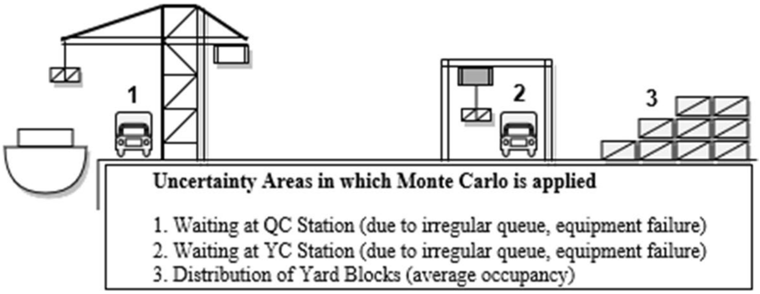

Fig. 3 Different phases of simulation

4.3 Stage 3 and 4: Truck operations time and carbon footprint aspects

Internal truck movements take considerable time and cause atmospheric emissions and other externalities both of which need to be limited in every responsible port environmental management. As said above, our objective(s) is to minimise truck operation time from each berth to container blocks and determine the number of containers to be carried to each container sub-block by satisfying all constraints. Distance data from each berth to each container sub-block is obtained from geographic information systems (GIS) equipment. The average truck speed is assumed to be 20 km/h. Thus, operation time is obtained. Truck idling times during crane handling at the berth and yard have already been calculated in the previous stage. Thus, total transportation time is calculated by summing three time factors. The carbon footprint of each truck is obtained by multiplying average fuel consumption per hour by the CO_2 emission factor, as shown in Table 3. Carbon footprint data of each truck were not readily available. However, fuel consumption data for both running and idling time are utilised to obtain carbon footprint values.

The problem is structured as a linear integer programming optimisation one since the objective function and constraints are linear and satisfy optimality conditions. The linear programming model for the minimisation problem can be defined as in Eq. 1:

Objective function	$\min Z = \left(C1_{ijk} + C2_{ijk} + C3_{ijk}\right)X_{ijk}$ (1)
Constraints	subject to
Vacant capacity constraint (Table 5) (Vacant capacity of container sub-blocks is an input)	$A_{ji} = \sum_{j=1}^{11} \sum_{i=1}^{18} \sum_{k=1}^{3} X_{ijk} \leq V_{ji}$ (18 × 11 matrix)
Max. container constraint for each block (Capacities of container blocks are not equal. Therefore, the number of trucks to be assigned is given equally for each block to avoid congestion.)	$B_j = \sum_{j=1}^{11} \sum_{i=1}^{18} A_{ij} \leq T_j$ (1 × 11 vector)
The total number of containers to be handled from ship to shore	$\sum_{j=1}^{11} \sum_{i=1}^{18} \sum_{k=1}^{3} X_{jik} = 1500$
Number of times each truck type is used (There are three types of trucks that differ from each other in terms of fuel consumptions and CO_2 emissions. There needs to be 1500 truck moves for 1500 containers. Truck allocation can be done accordingly.)	$D_k = \sum_{k=1}^{3} \sum_{j=1}^{11} \sum_{i=1}^{18} X_{kji} \leq Y_k$ (1 × 3 matrix)
Road blockage (between berths and sub-blocks.) (Berth 1 cannot reach sub-block 1,2,3) (Berth 2 cannot reach sub-block 5, 6, 7) (Berth 3 cannot reach sub-block 8, 10, 11)	Berth 1: $\left\{X_{1,1,1} : X_{18,3,3}\right\} = 0$ Berth 2: $\left\{X_{1,5,1} : X_{18,7,3}\right\} = 0$ Berth 3: $\left\{X_{1,8,1} : X_{18,8,3}\right\} = 0$ Berth 3: $\left\{X_{1,10,1} : X_{18,11,3}\right\} = 0$
	$X = \mathit{integer}$ and $X \geq 0$

i: number of sub-blocks (1:18)
j: number of blocks (1:11)
k: number of truck type (1:3)
C1: Idling time or carbon-footprint of the truck at berth
C2: Transportation time or carbon-footprint between berth (1,2,3) and container sub-block
C3: Idling time or carbon-footprint of the truck at sub-block
X: Number of containers to be transported to each sub-block by each truck type
V: Container sub-block vacancy matrix (Table 5)
T: Container block capacity vector (T = [272 272 272 312 312 312 312 312 312 312 312])
Y: Number of times of usage for each truck type vector (Y = [500 500 500])

Each objective is minimised in terms of time, and carbon footprint factors for three berths; namely, six minimisation problems are solved simultaneously to generate data for determining the best berthing solution for incoming ship. Besides, six different container allocations are made for each of the container sub-blocks according to each berth.

4.4 Stage 5: balancing sustainability dimensions

As detailed above, to select the optimum berth for an incoming ship, the relative importance (weights) the management ascribes to our two criteria (truck time and carbon footprint) must first be decided. The analytical hierarchy process (AHP) is used for this purpose. The decision-maker (DM) group we approached were highly experienced port managers, in C-level and senior level positions; their profiles are presented in Table 4.

AHP is a multi-criteria decision-making method developed by Thomas Saaty (Saaty 1994), and it is widely used in many applications concerned with decision-making. The method has a simple structure and is based on the pair-wise comparisons of criteria with a 1–9 Saaty scale. AHP data are obtained from the DM group.

Table 3 Carbon footprint data of trucks

Truck type	[a]Average fuel consumption while in operation (l/min)	[b]Average fuel consumption while idling (l/min)	CO_2 emission factor (lean and green Europe 2017) (kg CO_2/l)	Carbon footprint while in operation (kg CO_2/min)	Carbon footprint while in idling (kg CO_2/min)
Type 1	0.082	0.0403	3.2	0.262	0.12907
Type 2	0.098	0.0403	3.2	0.314	0.12907
Type 3	0.091	0.0403	3.2	0.291	0.12907

[a]Records of case container terminal

[b]U.S. Department of Energy (2015)

Table 4 Profiles of DM group

Number of participants	Position	Experience (years)	Graduate degree
1	CEO	10	MS
2	CEO	7	MS
3	COO	27	BS
4	Managing director	19	BS
5	Operation manager	7	BS
6	Operation manager	8	BS

4.5 Stage 6: selection of berth with MOORA method

Multi-objective optimisation based on ratio analysis (MOORA) is a multi-criteria decision-making technique for ranking a set of alternatives by a set of criteria. The method is proposed by Brauers and Zavadskas (2006) for privatisation projects. According to Stanujkic et al. (2012), MOORA is more straightforward in its application and less complicated than other MCDM methods. Moreover, it can be classified as both performance-based with ratio analysis, similar to COPRAS and SAW, and distance-based with reference point approach, identical to TOPSIS (Stanujkic et al. 2012). Akkaya et al. (2015) describe the MOORA method as having a very low computational time, straightforward application, minimum mathematical calculation, and good stability. Therefore, we decided to apply the MOORA ratio method together with the importance weights obtained from AHP analysis to rank alternative solutions to the berth allocation problem. Both methods (AHP and MOORA) have found applications in bank branch location (Görener et al. 2013), ERP system selection (Vatansever and Uluköy 2013), etc.[3]

5 Results

We have employed a multi-staged solution approach, consisting of discrete simulation, integer linear programming and multi-criteria decision-making. In this section, our findings from this analysis are discussed.

Monte Carlo simulation predicts the average vacant capacity of each sub-block where incoming containers could be transferred. Data on two hundred days of total vacant capacity and 30 days of the vacant capacity of each sub-block were collected. The simulation determines the average vacant spots in each sub-block where incoming containers can be stored. Results are shown in Table 5.

[3] The detailed MOORA calculation procedure is not given here, but it is carried out according to (Brauers and Zavadskas 2006) and is available from the authors upon request.

Table 5 Container blocks vacant capacity

Block Sub-block	B-1	B-2	B-3	B-4	B-5	B-6	B-7	B-8	B-9	B-10	B-11
S-1	30	22	14	20	8	16	0	0	3	40	51
S-2	0	0	0	0	0	0	66	14	0	22	36
S-3	28	44	4	29	2	2	48	0	3	63	17
S-4	0	39	0	0	0	0	77	41	0	25	34
S-5	3	3	6	5	45	2	53	55	7	64	54
S-6	0	0	0	0	22	0	54	2	0	30	38
S-7	7	4	4	35	37	2	52	0	7	45	43
S-8	0	0	0	55	59	0	62	5	0	42	7
S-9	3	12	16	2	5	47	34	0	12	27	61
S-10	0	0	68	0	61	31	0	48	0	62	41
S-11	3	33	3	7	7	57	57	2	48	35	41
S-12	0	7	0	0	55	4	49	0	38	37	39
S-13	3	68	4	26	10	0	51	48	3	44	42
S-14	0	9	0	54	0	3	56	6	0	43	53
S-15	7	0	32	58	2	0	58	0	42	48	48
S-16	0	7	24	11	0	55	45	48	52	47	44
S-17	0	0	57	0	2	2	8	5	2	54	32
S-18	0	3	4	11	0	0	0	0	0	47	62

Once vacant container sub-block capacity is obtained, Monte Carlo simulation is employed again to determine the queuing time of trucks (at quay and yard). Samples of 150 data points at each queue were collected. The probabilities of queuing times are presented in Table 6. Random samples were generated to obtain the queuing times, and these were added to truck transportation times (from berth to block).

Linear integer programming is utilised to determine the minimum transportation time and minimum CO_2 emissions from each berth to container blocks. Six problems are set to solve two different minimisations for three berths. Minimum time and emissions are derived, together with the distribution of incoming containers to sub-blocks by type of truck. The solution for truck time minimisation in berth-1 is shown in Table 7. For instance, 51 containers are transported to sub-block 1 of block 11 with type-2 trucks, and 17 containers are transported to sub-block 3 of block 11 with type-3 trucks, which have lower fuel consumption and CO_2 emissions than type-2 trucks.

The remaining five other solutions are not shown in detail but in summary, as in Table 8. The first three rows of that table are the results of time minimisation problems and their corresponding carbon footprint values. The next three rows are the results of carbon-footprint minimisation problems and their corresponding time values. For instance, when an incoming ship is berthed at berth-1, and the problem is to minimise the time of internal truck operations, the solution yields 7471.32 min, and the corresponding CO_2 emission is 1423.25 kg.

Table 6 Probability distribution of queuing time at quay- and yard-crane

Quay-crane		Yard-crane	
Probability (%)	Time (min)	Probability (%)	Time (min)
1.33	0.75	4.00	1.00
4.67	1.00	12.67	1.25
16.00	1.25	13.33	1.50
18.00	1.50	14.67	1.75
20.67	1.75	17.33	2.00
16.00	2.00	12.67	2.25
8.00	2.25	6.00	2.50
8.67	2.50	5.33	2.75
3.33	2.75	5.33	3.00
3.33	3.00	4.67	3.25
		4.00	3.50

Table 7 Numbers of containers transported from berth 1 to each sub-block with time minimisation

Sub-block	Block-1			…	Block-11		
	Truck type						
	Type-1 truck	Type-2 truck	Type-3 truck	…	Type-1 truck	Type-2 truck	Type-3 truck
1	0	0	0	…	0	51	0
2					0	36	0
3					0	0	17
4					0	34	0
5					0	0	0
6					0	0	38
7					0	0	0
8					0	0	7
9					61	0	0
10					41	0	0
11					0	0	0
12					0	0	0
13					0	0	0
14					0	0	0
15					0	0	0
16					27	0	0
17					0	0	0
18					0	0	0
Minimum time	7471.32 min						
Corresponding CO_2 emission	1423.25 (kg CO_2)						

Table 8 Linear integer programming results

Scenario	Time (min)	Carbon footprint (kg CO_2)
Berth 1 (min time)	7471.32	1423.25
Berth 2 (min time)	8091.31	944.85
Berth 3 (min time)	8235.33	923.60
Berth 1 (min CO_2)	7513.25	1402.12
Berth 2 (min CO_2)	8711.12	890.06
Berth 3 (min CO_2)	8718.31	838.65

Table 9 Multi-objective optimisation results

Scenario	Ranking
Berth-1 (min Time)	6
Berth-2 (min Time)	2
Berth-3 (min Time)	3
Berth-1 (min CO_2)	5
Berth-2 (min CO_2)	4
Berth-3 (min CO_2)	1

AHP is used to determine the weights of 'truck time' and 'carbon footprint' (Table 4). Truck time is deemed to be slightly more important (54.57%) vis à vis carbon footprint (45.43%). In the last stage, a multi-objective optimisation method, MOORA, is utilised, together with the AHP weights above, to select the optimum alternative berth for the incoming ship. The rankings of the alternative solutions are shown in Table 9.

Therefore, berth 3 with CO_2 minimisation gives the optimum result when the time and carbon footprint criteria are taken into account. Incoming containers are distributed to the sub-blocks as shown in Table 10.

A series of analyses from stages 2 to 6 are carried out to eliminate the deviation of randomness that results from the determination of truck waiting times in the queue. In stage 2, random waiting times are generated according to the probability distribution of collected waiting times of trucks, and these queuing times are added to the total time of truck operations. However, the generated random waiting times change in each iteration and create a minor deviation in the result of subsequent stages. Therefore, we repeat the problem from stage 2 to 6 a total of 15 times to see how this deviation affects the decision. From the MOORA method, the rankings for each repetition are shown in Fig. 4.

As seen in Fig. 4, even though there exists a minor deviation for the first three alternative solutions, the last three solutions do not change.

An operations manager can thus consider 'berth-3 carbon footprint minimisation solution' as the first option (10 times out of 15 iterations in #1 position), and 'berth-3 time minimisation solution' as the second option (8 times out of 15 repetitions as #2 position) for an incoming ship. Both scenarios provide effective solutions to a

Table 10 Number of containers transported from berth 3 to each sub-block with carbon footprint minimisation

	Block-1			…	Block-11		
Sub-block	Truck-type						
	Type-1 truck	Type-2 truck	Type-3 truck	…	Type-1 truck	Type-2 truck	Type-3 truck
1	0	30	0	…	0	0	0
2		0	0				
3		28	0				
4		0	0				
5		3	0				
6		0	0				
7		7	0				
8		0	0				
9		3	0				
10		0	0				
11		3	0				
12		0	0				
13		3	0				
14		0	0				
15		0	7				
16		0	0				
17		0	0				
18		0	0				
Minimum CO_2 emission	838.65 (kg CO_2)						
Corresponding time	8718.31 min						

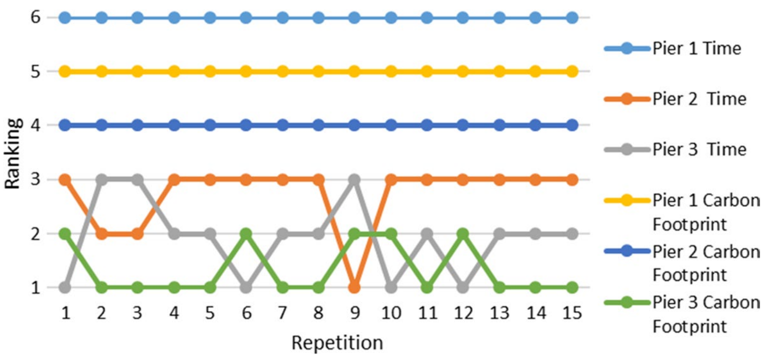

Fig. 4 Rankings comparisons for each repetitive solution

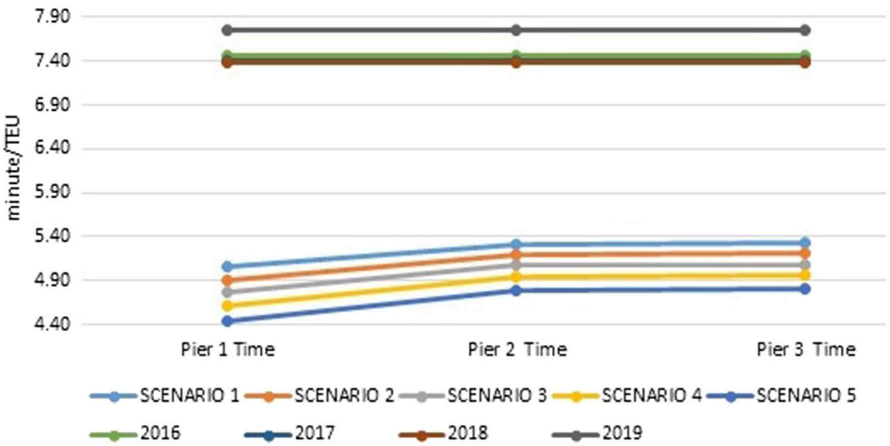

Fig. 5 Time efficiency of the optimisation problem

manager who wants to balance truck time and CO_2 emissions. Our analysis shows that the results are consistent for each repetitive solution. The critical point here is that the values given in Table*** are calculated on a single truck basis. For the optimal solution, considering that ten terminal trucks are used, the total unloading time of the 1500 TEU container ship will be (8718.31 / 10 = 871.83 min). The number of vehicles assigned to the vessel will vary depending on how many resources the terminal is willing to allocate. It should be noted, however, that the ranking of the alternatives can change depending on operational and environmental policies of the different terminals, the approaches of the decision-makers, and the number of containers to be unloaded and moved to vacant blocks.

Once the stability of the methodology is ascertained through repetitive analysis, five transportation scenarios are created to demonstrate the efficiency and effectiveness of the proposed approach. In each scenario, the number of incoming containers is varied from 500 to 1500, with an increment of 250. Then, each scenario is

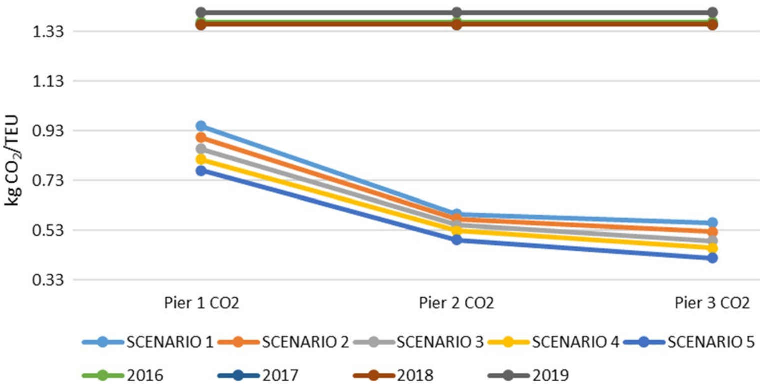

Fig. 6 CO_2 emissions efficiency of the optimisation problem

optimised six times for each berth (berth 1, 2 and 3). In the first three optimisations, total time is minimised. In the next three optimisations, total CO_2 emissions is minimised. Each total value (time and CO_2) is rated with the total number of containers, and the units are converted to show minutes/TEU and kg CO_2/TEU. To benchmark the efficiency of the solutions for each scenario, the terminal's average time productivity and its corresponding CO_2 emission values are used from 2016 to 2019.

The average truck operating time from berth to the yard varies from 7.40 to 7.76 min between 2016 and 2019. According to our optimisation results, these values range from 4.44 to 5.34 min, including each berth at five scenarios as in Fig. 5. Therefore, time efficiency improves between 27.8% and 42.8%.

The average truck CO_2 emissions from the berth to the yard varies between 1.36 and 1.40 kg between 2016 and 2019. According to our results, this value ranges from 0.42 to 0.95 kg CO_2, including each berth at five scenarios as in Fig. 6. Therefore, CO_2 emissions efficiency improves between 30.1% and 70.3%

6 Conclusions

We have combined Monte Carlo simulation, integer linear programming and multi-criteria decision-making methods in a multi-staged solution to address several research objectives. Specifically, we have established the average vacant capacity in yard blocks, the queuing times of trucks at berth and yard and the distribution of incoming (import) containers to blocks by type of truck, satisfying minimum time and carbon footprint goals, the relative importance (weights) of truck time and carbon footprint in our optimisation exercise and, finally, on the basis of the above, the optimum berth allocation for an arriving ship.

Many of the problems that may arise during container terminal operations are unpredictable, for instance uncertainty in the arrival of ships. Deterministic methods for the solution of terminal-related problems are, therefore, often questioned in view of the many uncertainties involved in terminal operations. For instance, the selection of berths in modern container terminals can become a rather complex problem due to the many factors involved. These include the container blocks occupation, irregular vehicle queuing at the yard- and quay-crane stations, failure-induced waiting and so on. Therefore, we have approached the berth selection problem with a multi-stage operations research model in which different optimisation methods are integrated with three discrete probabilistic models. The most important contribution of this study to the literature is that our model provides an optimum solution between time costs and environmental costs – an optimum balance was established between these two factors.

Once our approach is proven to be valid through repetitive analysis, the efficiency and effectiveness of our methodology are demonstrated with five transportation scenarios. The rated time and CO_2 emissions values from each scenario are compared with those of the terminal from 2016 to 2019. We show that time efficiency is improved between 27.8 and 42.8%, and CO_2 emissions efficiency is improved between 30.1 and 70.3%.

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